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Influence and seepage: An evidence-resistant minority can affect public opinion and scientific belief formation

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Abstract

Some well-established scientific findings may be rejected by vocal minorities because the evidence is in conflict with political views or economic interests. For example, the tobacco industry denied the medical consensus on the harms of smoking for decades, and the clear evidence about human-caused climate change is currently being rejected by many politicians and think tanks that oppose regulatory action. We present an agent-based model of the processes by which denial of climate change can occur, how opinions that run counter to the evidence can affect the scientific community, and how denial can alter the public discourse. The model involves an ensemble of Bayesian agents, representing the scientific community, that are presented with the emerging historical evidence of climate change and that also communicate the evidence to each other. Over time, the scientific community comes to agreement that the climate is changing. When a minority of agents is introduced that is resistant to the evidence, but that enter into the scientific discussion, the simulated scientific community still acquires firm knowledge but consensus formation is delayed. When both types of agents are communicating with the general public, the public remains ambivalent about the reality of climate change. The model captures essential aspects of the actual evolution of scientific and public opinion during the last 4 decades.

Influence and seepage: An evidence-resistant minority can affect public opinion and scientific belief formation

More than 150 years ago, John Tyndall demonstrated experimentally that "carbonic acid", despite being a perfectly colorless and invisible gas, was able to absorb heat radiation. Unlike the atmosphere, carbonic acid was nearly opaque to radiant heat. We now refer to carbonic acid as CO_2, and following on the heels of Tyndall's discovery, it was recognized more than a century ago that industrial CO_2 emissions may alter the Earth's climate (Arrhenius, 1896). During the last two decades, the evidence that humans are altering the climate has become unequivocal. There is near unanimity (around 97%) among domain experts that the climate is changing due to emissions of CO_2 and other greenhouse gases, mainly from combustion of fossil fuels (Anderegg, Prall, Harold, & Schneider, 2010; Cook et al., 2013, 2016; Doran & Zimmerman, 2009; Oreskes, 2004). The Intergovernmental Panel on Climate Change (IPCC) periodically summarizes the scientific consensus in Assessment Reports (e.g., most recently AR5; IPCC, 2013).

Notwithstanding this pervasive scientific agreement, the public in some countries continues to be divided on whether or not climate change presents a real risk and is caused by fossil-fuel combustion. For example, Carmichael and Brulle (2017) showed in an analysis of 74 surveys (between 2002–2013) that public concern with climate change in the U.S. peaked in 2008 but then declined until 2011. Although the relevance of those fluctuations in opinion is subject to debate (e.g., Egan & Mullin, 2017), there is no doubt that currently many Americans (around 36%; Egan & Mullin, 2017) are not worried about climate change, and that a similar number or more do not accept its human origins (Hamilton, Hartter, Lemcke-Stampone, Moore, & Safford, 2015). The public also widely underestimates the extent of the scientific consensus. As of 2016, less than 70% of the public recognize that most scientists agree on climate change, although that share has increased from 50% in 2010 (Hamilton, 2016).

The reasons for the discrepancy between the scientific agreement and the public's low concern are well understood. Brulle, Carmichael, and Jenkins (2012) showed that public opinion is guided by elite cues and mobilization of advocacy groups, with media coverage being an important conduit of that influence. There is abundant evidence for the existence of a well-organized campaign that seeks to undermine the public's understanding of climate change (e.g., Dunlap & McCright, 2011; Dunlap, 2013; McCright & Dunlap, 2003, 2010; Medimorec & Pennycook, 2015; Oreskes & Conway, 2010). Analysis of IRS data puts the income of a network of conservative think tanks at somewhere near $1 billion annually (Brulle, 2013). At least in part, this network is dedicated to questioning the scientific consensus on climate change.

The effects of that funding are detectable in a number of ways. The vast majority of books (over 90%) that are critical of mainstream climate science are linked to conservative think tanks (Dunlap & Jacques, 2013; Jacques, Dunlap, & Freeman, 2008). The influence on public discourse of two core funders—ExxonMobil and the Koch family foundations—was identified in a network analysis by Farrell (2015). Organizations that received fundings from those two entities were significantly more central to the network than individuals or organizations without such funding. Moreover, Farrell found that the semantic similarity between the output of this denial network and coverage in the mainstream media increased between 1993 and 2013. A similar increase was observed in the speeches of U.S. presidents, albeit at a lower level of similarity overall. Although the direction of causality cannot be ascertained from those data, one interpretation is that the efforts of conservative think tanks (Brulle, 2013) and Exxon (Supran & Oreskes, 2017) had the intended effect of shaping public discourse with denialist talking points, thereby delaying meaningful mitigation efforts.

In particular, the denialist campaign is likely to be behind the public's under-estimation of the consensus among scientists (Hamilton, 2016). This is more than a mere miscalibration, given that appreciation of the consensus has been identified as a "gateway" belief that determines people's policy support (van der Linden, Leiserowitz, Feinberg, & Maibach, 2015). When people are educated about the scientific consensus in experiments, this has been repeatedly shown to increase people's acceptance of the underlying science (Lewandowsky, Gignac, & Vaughan, 2013; S. L. van der Linden, Clarke, & Maibach, 2015; S. van der Linden, Leiserowitz, & Maibach, 2018). Conversely, a single dissenting opinion has been shown to be sufficient to reduce people's beliefs in the adequacy of scientific evidence to guide government policy (Koehler, 2016; see also Bovens & Hartmann, 2004). The creation of a chimerical scientific debate is thus an effective trigger of cognitive mechanisms that are likely to disengage the public and reduce their demands for policy action.

In addition to these effects of organized denial on the public and political spheres, there are indications that contrarian activity has also affected the scientific community itself. Freudenburg and Muselli (2010) showed that the IPCC's consensus report (AR4 at the time) had been too conservative rather than too alarmist, as revealed by an analysis of media coverage of subsequent new scientific findings. Further confirmation of the IPCC's conservatism was provided in a textual analysis by Medimorec and Pennycook (2015), which found that the IPCC (AR5) used more cautious and uncertain language than documents produced by a conservative think tank committed to denying the scientific consensus.

Other work has identified the "reticence" of scientists to confront the full implications of their findings (Hansen, 2007), their propensity to "err on the side of least drama" (Brysse, Oreskes, O'Reilly, & Oppenheimer, 2013), and their concern of being portrayed as "alarmist" (Risbey, 2008) as factors that might lead the scientific community to paint risks in a less dramatic light. A recent extension of this argument suggested that denial may have "seeped" into the scientific community itself (Lewandowsky, Oreskes, Risbey, Newell, & Smithson, 2015). Lewandowsky et al. identified several known psychological processes, such as stereotype threat or pluralistic ignorance, that might render scientists' work vulnerable to contrarian attacks which are often toxic and personal (Lewandowsky, 2019; Mann, 2012). One avenue of attack involves freedom-of-information (FOIA) requests, typically for scientists' personal emails. Depending on jurisdiction, these requests may result in the release of thousands of emails between researchers, which are then quote-mined for compromising statements. There is evidence that personal emails between scientists can be exploited in this manner with a discernible impact on public opinion (Stoutenborough, Liu, & Vedlitz, 2014). Ley (2018) analyzed the impact of FOIA requests on scientists through in-depth interviews. He found that all respondents had altered their means of communication in response to an FOIA requests, with many scientists engaging in self-censorship and others resorting to phone calls. A minority also reported a chilling effect on their ability to express research ideas. The self-censorship that results from FOIA requests may be just one avenue by which pressure from political operatives could shape scientists' interpretation of data notwithstanding their commitment to reject denialist talking points. Lewandowsky, Oreskes, et al. (2015) illustrated the possibility of such "seepage" within the context of the recent presumed "pause" or "hiatus" in global warming.

The "pause" refers to a period of slower-than-average warming, which is alleged to have occurred from around 1998 for around a decade, and which climate contrarians seized on to claim that global warming has "stopped" (e.g., Carter, 2006). Boykoff (2014) showed how the media and other public actors used the apparent slowdown in warming to create a frame for discussion around the notion that warming had unexpectedly "stopped" or "paused." Statistical evidence for a "pause" or a significant slowdown is scarce or non-existent (Lewandowsky, Risbey, & Oreskes, 2015; Lewandowsky et al., 2018; Risbey et al., 2018), and the notion of a "pause" has been identified as misleading in a blind expert test (Lewandowsky, Risbey, & Oreskes, 2016). Nonetheless, the scientific community responded to the fluctuation in warming rate with, to date, more than 200 peer-reviewed publications (Risbey et al., 2018). A number of those articles framed the "pause" as a challenge to the mainstream scientific view of greenhouse-driven global warming (see Lewandowsky, Risbey, & Oreskes, 2016, Table 2). Lewandowsky, Oreskes, et al. (2015) argued that the scientific community's concern with a short-term fluctuation in warming rate was likely amplified—or even generated—by the rhetoric of contrarian political operatives and their allies. However, Lewandowsky, Oreskes, et al. could only provide circumstantial evidence to buttress their argument.

This article explores the seepage notion within a quantitative theoretical approach. We present an agent-based model of the three principa groups of actors: the scientific commmunity, operatives in the organized denial network, and the public at large. All actors are represented by rational Bayesian agents that seek information by inspecting climate data or by communicating with each other. We design our agents to be Bayesian not only because people's decisions can conform to Bayesian norms of rationality (e.g., Griffiths, Kemp, & Tenenbaum, 2008; Lewandowsky, Griffiths, & Kalish, 2009), but in particular because even seemingly "irrational" behaviors can emerge from Bayesian principles. For example, belief polarization (Cook & Lewandowsky, 2016; Jern, Chang, & Kemp, 2009) can be accommodated within a rational Bayesian framework, and it has been shown that Bayesian agents can form persistent "echo chambers," enclosed epistemic bubbles in which agents share most beliefs (Madsen, Bailey, & Pilditch, 2018). The use of rational agents also seemed advisable in light of several suggestions that climate denial can be considered a rational enterprise (Cook & Lewandowsky, 2016; Lewandowsky, Cook, & Lloyd, 2016), notwithstanding its wholesale dismissal of scientific evidence.

We seed the model with the global temperature data from 1950 through 2017, sampling new observations on an annual basis. During each simulated year, the agents communicate with each other and update their belief in the hypothesis that the Earth is warming. The simulations below were designed to answer the following questions: (1) In the absence of organized denial, how quickly would the scientific community have settled on the consensus position that greenhouse-driven warming exists? (2) Given the strength of evidence for warming, how can rational agents remain resistant to the evidence and continue to deny climate change? (3) What are the effects of denial on the scientific community? In particular, is there evidence for "seepage"? (4) What are the effects of denial on the public at large? In particular, can actual public opinion be modeled without disproportionate representation of denialist messages by the media (e.g., in the name of balance)?

The Model

Climate data input

The model had access to two global temperature datasets: The HadCRUT4 product curated by the U.K. Met Office (Morice, Kennedy, Rayner, & Jones, 2012) and the GISTEMP dataset produced by NASA's Goddard Institute for Space Studies (Hansen, Ruedy, Sato, & Lo, 2010). Both datasets record global mean surface temperature (GMST), expressed as anomalies from a climatological baseline. For the purposes of detecting changes in global climate, individual temperature observations are converted into deviations from a long-term average temperature (typically across 30 years) for the station in question. Those deviations, known as anomalies, are then averaged in an area-weighted manner across all locations around the world to estimate global temperature trends. Figure 1 shows GMST anomalies for the two datasets. Both datasets show that the Earth has been warming continuously since around 1970. The "pause" period refers to the apparent decrease in warming rate during the decade after 1998. The figure also clarifies that this period is now clearly over, given the recent sharp up-tick in temperature.

Although both datasets display very similar long term trends, when the same data are instead represented as trends of varying durations, some differences between datasets emerge. Figure 2 shows trends for HadCRUT4 (panel A) and GISTEMP (panel B). Each panel shows the warming trends that were observable, given the available data at the time, for any vantage point between 1984 and 2016 (horizontal axis). For each vantage point, between 3 and 25 years were included in the trend calculation (vertical axis) by moving backwards in time. Significant trends are indicated by a dot. For example, the entries for the final column in each panel record the trend values that were observable in 2016, considering anywhere between the preceding 3 years (bottom row; 2014–2016) and 25 years (top row; 1992–2016).

Figure 2 clarifies that at any time since 1989, a significant warming trend was detectable if a sufficiently large number of observations was included. However, the figure also shows that if a small number of years is considered, trend values can fluctuate considerably and may in some cases even be negative. Those small-scale fluctuations are of no climatological relevance but offer an opportunity for contrarians to claim that global warming has "stopped" or "paused". It is also apparent from the figure that the notion of a "pause" during the decade following 1998 was more visible with the HadCRUT dataset (panel A) than GISTEMP (panel B). The reasons for this are well understood: Unlike GISTEMP, HadCRUT does not record observations for much of the Arctic, the region of the globe that is known to warm most rapidly. When those coverage gaps are corrected by interpolation (Cowtan & Way, 2014), the divergence betweent HadCRUT4 and GISTEMP is largely eliminated (e.g., Lewandowsky, Risbey, & Oreskes, 2015; Risbey et al., 2018).

Our model simulated the gradual acquisition of scientific knowledge about climate change by a population of agents that continually examined the most recent temperature trend available at any given time. The number of years being considered by each agent was a model parameter, described below. Agents then communicated their perceptions of the data to each other, updating their prior beliefs with the new evidence and communications at each round. The top panel in Figure 3 provides a graphical overview of the model.

Classes of agents

The model comprised three classes of agents, representing mainstream scientists, contrarians, and the general public. One or more of those classes of agents was active in any given simulation. The proportions of scientists to contrarians, along with their representation in communicating to the public was manipulated between simulations.

Scientists and contrarians

Scientists and contrarians started with a prior belief in anthropogenic climate change of 1%, $P(CC) = .01$. Thus, all agents commenced from a position of strong skepticism of the global-warming hypothesis. The agents then sampled information from the real world by inspecting the climate data (HadCRUT or GISTEMP), and then updating their belief in climate change according to either an unbiased (scientists) or biased (contrarian) interpretation of temperature trends. Data sampling occurred annually. In between data sampling, scientists and contrarians communicated both among themselves (passing on trend information) and to the general public (passing on interpretations of the data), such that recipients of these communications further updated their belief in climate change (details below). Scientists and contrarians had the same functionality but differed in their settings of three parameters that defined each class of agents.

Dataset preference. This parameter, DSP_S and DSP_C, represented the dataset (GISTEMP or HadCRUT) from which the agent drew data-points. This preference remained constant across the simulation run.

Memory window. The memory window parameter (M_S for scientists and M_C for contrarians, respectively) determined how many historical temperature observations agents considered as they inspect the data at each iteration to compute a warming trend. That trend constituted the latest evidence for climate change available to the agent. M varied between 3 and 30 and differed between scientists and contrarians. For scientists, M_S was typically set to 15 or 30, representing climatological practice to ignore short-term fluctuations. For contrarians, M_C was typically set to 3, reflecting the fact that denialist arguments pervasively rely on "cherry-picking" of short-term trends (Lewandowsky, Ballard, Oberauer, & Benestad, 2016). If an agent possessed a full memory window, new data points supplanted the oldest.

Skew. The skew parameter represented an interpretative bias by determining the degree to which temperature trends were skewed by the agent during processing. Positive values of skew bias the agent against climate change, negative values towards climate change, whereas a value of 0 represented unbiased processing (see Equation 1 below). For scientists, S_S was set to 0 (unbiased processing) in all simulations. For contrarians, S_C, was typically set to positive values, reflecting a bias against detection of climate change.

All parameters were set uniformly across all agents within a class for a given simulation run.

General public

All general-public agents were also skeptical initially, with a prior belief in anthropogenic climate change of 1%, $P(CC) = .01$. Unlike contrarians and scientists, the general-public agents do not draw information directly from any datasets. This reflects the likely fact that members of the public do not read the scientific literature but rely on interlocutors—represented here by scientific and contrarian voices channeled via the media—to inform themselves about climate change.

In all simulations, general-public agents were passive listeners whose sole function was to receive interpretations of the data, and update their belief in climate change accordingly (see Equation 2 below). For all simulations including the general public, 1,000 such agents were initialised.

Initialization and evolution over time

All simulations entailed the initialisation of 1000 agents (scientists and/or contrarians), each starting with $P(CC) = .01$. Agents initially drew a sample of three data-points from the chosen dataset into their memory, starting at the specified year of data. For instance, an agent drawing from the GISTEMP dataset with a specified start year of 1950 would draw the data points (GMST anomalies) for 1950, 1951, and 1952 into their initial sample in memory. Those 3 data points enabled the agent to compute the first regression slope (1950-1952). No updates were made based on this initial sample. The initial sample instead set the prior for going forward to all subsequent belief-updating steps.

Data sampling

Data sampling occurred annually (see top panel in Figure 3). Scientists and contrarians sampled a single data-point from their preferred dataset for the current year, adding it to the observations already in their memory window. Thus, for the above example, an agent would add the observation for 1953 to the memory window when an observation for that year became available, and so on. Once data had been sampled, the agents then calculated a standard regression slope, β, from the data points in their memory window (as illustrated in Figure 2). This trend represented the change in temperature up until the present year, going back as far as their memory window allows. Figure 4 illustrates this process for two hypothetical agents with two different sizes of memory window.

A given value of β obtained during data sampling was retained by the agent throughout the 5 communication events, described below, that were presumed to occur during the same year.

Updating beliefs from data

The calculated regression slope, β, was then interpreted as a Likelihood Ratio (LR) that provided evidence for (or against) the climate change hypothesis as follows:

$$LR = 10^{\beta - S}, \tag{1}$$

where the more positive the slope (β), and the lower the skew parameter (S), the larger the LR value. If the $\beta - S$ term is > 0 (and thus the slope is still considered positive, having taken into account a potentially biased interpretation), the LR is > 1, indicating support for the climate change hypothesis. In the same manner, if the $\beta - S$ term is equal to zero (and no positive trend is perceived, having taken into account a potential bias), the LR value is 1, representing complete ambiguity. Finally, if $\beta - S$ is negative, the LR is < 1, indicating support against the climate change hypothesis. This process of computing the LR ensured that agents could encounter evidence either for or against the climate-change hypothesis. Unless a bias was introduced by setting S to a non-zero value, our agents were not predestined to inevitably settle either on endorsement or rejection of the hypothesis. Figure 5 illustrates this process.

The LR values are then plugged into the log-odds form of Bayes theorem to update the belief in climate change via Bayesian belief revision, as follows:

$$\frac{P(CC|E)}{P(\neg CC|E)} = \frac{P(CC)}{P(\neg CC)} \times LR. \tag{2}$$

The odds on the right-hand side of the equation represent the agent's beliefs in the climate change hypothesis (CC) and its complement, namely that there is no climate change ($\neg CC$). The odds on the left-hand side of the equation represent the updated beliefs in the two competing hypotheses, given the evidence (E) just introduced by the likelihood ratio (LR).

Communication rounds

Each data sampling event was accompanied by 5 communication rounds (see top panel, Figure 3), during which the agents exchanged information. This mimicked the idea that although annual data become available once a year, scientists repeatedly exchange their views about those data throughout the year. Depending on the simulation, communication could occur just among scientists (S) and contrarians (C) involving all possible pairings (i.e., $S \rightarrow C$, $S \rightarrow S$, $C \rightarrow C$, and $C \rightarrow S$), or additionally also from scientists and contrarians to the general public. The manipulation of the communication regime permitted selective tests of mechanisms within the scientific community (e.g., seepage) as well as mechanisms involving the public (e.g., contrarian influence). At each round, each agent (when present) received exactly one communication according to the following rules.

Selection of communicators. For each of the 5 communication rounds, a random sample of scientists (and contrarians, when present) were selected to be communicators. Sampling was with replacement, so the same agent might be involved in communicating on more than one occasion. The selection of a pool of communicators permitted manipulation of the proportion of scientists and contrarians in the pool independently of their prevalence in the population (see next section). The number of agents in each pool was $N = 10$ (Simulation 1), $N = 5$ (Simulation 2), and $N = 100$ (Simulations 3 and 4).

Communication among scientists and contrarians. When scientists or contrarians communicate among themselves, a random communicator from the pool passes on their latest slope estimate obtained during data sampling (β) to a random recipient agent, until all scientists and contrarians in the simulated population have received exactly one value. Recipients then interpret this slope via Equation 1 (thereby introducing their own bias), before updating their belief in climate change via Equation 2. Communicators are sampled with replacement from the pool so each communicator may be involved in more than one communication.

Communication to the general public. When scientists and contrarians communicate to the general public, a random communicator passes on their latest LR value (Equation 1) to a random member of the public, until all members have received exactly one value. The recipients directly update their belief in climate change using their received LR value via Equation 2.

The public therefore receives the interpretation of the data made by the interlocutors, rather than the original data. This reflects the fact that scientists (and contrarians) do not communicate the exact values of decadal warming trends to the public, but their interpretation of those trends. We additionally model the potential amplifying effects of the media by varying the representation of contrarians in communications independently of their actual number (see next section).

General simulation settings and manipulations

Several further system-wide simulation parameters were manipulated:

StartYear: Time from which the data sampling process starts. Set to 1950 throughout.

ConProp: Proportion of agents that are categorized as contrarians (the remainder being mainstream scientists). In reality, this proportion has been estimated at no more than .03 (3%) of practicing climate scientists across numerous studies (summarized by Cook et al., 2016). Any value greater than 3% thus models the inclusion of other contrarian operatives, such as bloggers or think tanks, who are known to vocally publicize their own interpretations of the data (Farrell, 2016).

ConRep: The proportion of contrarians represented in the pool of communicators. There is evidence that contrarians tend to receive disproportionately more exposure in the media (Verheggen et al., 2014), presumably because the media seek to "balance" competing voices (Boykoff & Boykoff, 2004). If 3% of the population of agents are contrarian, the communicator pool could either be representative (100 communicators, of which 3 are contrarian), or over-representative (e.g., 6 contrarians—double their prevalence in the population).

All simulations run until the entire historical temperature record (through the end of 2017) has been observed by agents, and the last 5 rounds of communication have been completed. Each simulation experiment involved 100 independent replications within each cell of the experimental design. The dependent variable of greatest interest in all experiments was the belief in climate change, $P(CC)$, over time, split by agent group and averaged across the 100 replications within each experimental cell. The model was programmed in Netlogo (version 6.0.1) and simulations were run using the RNetlogo package in R (Thiele, 2014). The Netlogo source code and output from all simulations is available for download at `https://github.com/StephanLewandowsky/ABM-seepage-and-influence`. The bottom panel in Figure 3 provides an overview of the 4 simulation experiments and indicates their purpose.

Simulation Experiment 1: Scientific consensus formation

The first simulation described how a scientific community builds a consensus belief around climate change by examining and discussing the data over time, and how that consensus is communicated to the public. In this simulation, all agents were unbiased

($S_S = 0$) and the two principal independent variables were the choice of dataset (GISTEMP vs. HadCRUT) and memory size. Memory size was variously set at 3, 10, 15, and 30. The largest memory size (30 years) corresponds to the length of climatological baseline that is taken to exceed the duration of short-term fluctuations and reveals greenhouse-gas driven warming (Medhaug, Stolpe, Fischer, & Knutti, 2017). The intermediate trend lengths (10 and 15 years) are diagnostic of short-term fluctuations and are therefore also often considered in the literature (e.g., Risbey et al., 2018). The shortest trends (3 years) are scientifically meaningless but are included for comparison, to show the effects of short-term variability on knowledge accumulation over time.

The first run of the experiment (Figure 6) did not include the general public. The figure traces the scientific community's emerging confidence in the proposition that the Earth's climate is changing. Several observations can be made. First, by around 2000, the community had settled on the climate-change hypothesis with virtual certainty, irrespective of the dataset being used and irrespective of the trend duration being considered. Second, as expected, with the (unrealistically) small memory size ($M_S = 3$), the collective belief fluctuated more widely, although it also converged on certainty. This reflects the fact that notwithstanding short-term fluctuations (positive or negative), a rational Bayesian agent will accumulate knowledge over time, and hence the impact of short-term fluctuations (represented by the likelihood ratio; LR in Equation 2) will have decreasing influence as belief in climate change consolidates (odds on the right-hand side of Equation 2). The ongoing updating of the posterior means that, although the memory buffer is constantly being updated and earlier memories are forgotten, the new prior (yesterday's posterior) is higher (if temperatures go up generally) than, say, 5 years ago. So at any moment, there is a latent, if not explicit, memory of global warming represented in the prior for that updating step. Third, GISTEMP supported faster consensus formation than HadCRUT. This was not unexpected given the coverage biases of HadCRUT that are known to have underestimated warming (Cowtan & Way, 2014).[1]

It is informative to align the results in Figure 6 with the chronology of the IPCC consensus statements (vertical dashed lines). The IPCC's First Assessment Report (FAR) from 1990 acknowledged that warming appeared to be underway, and stated that "The size of this warming [0.3° to 0.6°] is broadly consistent with predictions of climate models, but it is also of the same magnitude as natural climate variability. . . . The unequivocal detection of the enhanced greenhouse effect is not likely for a decade or more." In fact, it took less than a decade. The second assessment report (SAR), published in 1996, stated that "The balance of evidence suggests a discernible human influence on global climate." By 2001, the third assessment report (TAR) reported "There is new and stronger evidence that most of the warming observed over the last 50 years is attributable to human activities." The AR4 in 2007 concluded that "Warming of the climate system is unequivocal" and that "Most of the observed increase in global average temperatures since the mid-20th century is very likely due to the observed increase in anthropogenic greenhouse gas concentrations." Finally, AR5 in 2013 reiterated that "Warming of the atmosphere and ocean system is unequivocal", and additionally stated that "It is extremely likely that human influence has been the dominant cause of observed warming since 1950, with the level of confidence having increased since the fourth report." Those evolving scientific consensus statements map well onto the simulated temporal increment of belief. While this does not provide a quantitative test of the model, it shows at least qualitative convergence between the model and the scientific community.

The second run of the experiment included 1,000 agents that represented the general public but was identical to the first run in all other respects (with $M_S = 15$). The results are shown in Figure 7, indicating that the general public will absorb the information provided by the scientific community and will converge on the same scientific consensus, albeit with a delay. The delay reflects the fact that the general public does not have access to the raw data, relying instead on receiving communications from the scientists. The total number of information sources is thus reduced relative to the information available to the scientists themselves.

The results of simulation experiment 1 are straightforward and largely unsurprising: given the evidence available, the scientific community converges onto a consensus position. When the public benefits from the scientific information, they too acquire the consensus position through communication alone. Both runs of simulation experiment 1 only included unbiased agents. The remaining simulation experiments explore the operation and impact of denial in various contexts.

Simulation Experiment 2: Motivated denial

Simulation experiment 2 examined the process of denial. We particularly wanted to identify the conditions that are necessary for a rational Bayesian agent to avoid acquiring a belief in the hypothesis that climate change is real. One known way in which contrarians seek to mislead the public is by focusing on short-term temperature fluctuations (Lewandowsky, Ballard, et al., 2016). For example, the claim that global warming had "stopped" first arose in 2006, based on 8 years of data (Carter, 2006). This experiment therefore manipulated the size of the memory window, with M_C set to 3, 5, and 10. Based on the results of the first experiment, we expected such short-term focus to be insufficient to induce denial in our rational agents. We therefore also manipulated the agents' bias (see Equation 1) by setting $S_C = .015$ in one condition. This bias effectively prevented an agent from detecting any but the most extreme short term warming trends.

Figure 8 displays the results. Consider first the top row of panels, which represents unbiased agents ($S_C = 0$). It is clear that irrespective of memory size, unbiased agents cannot avoid acquiring belief in climate change. However, this behavior does not capture the actual nature of denial, which has exhibited persistence across many decades. An analysis of more than 16,000 contrarian documents revealed that organized denial continued unabated during the period 1998 through 2013 (Boussalis & Coan, 2016) . This stability of denial is reflected in the bottom panels of Figure 8. Irrespective of memory size, those agents never accept the hypothesis of climate change, owing to their biased interpretation of the evidence ($S_C = .015$).

The second experiment clarified that persistent denial in Bayesian agents becomes possible only through the introduction of a bias. A focus on short-term trends by itself is insufficient to prevent endorsement of the climate change hypothesis. We next consider what happens when a share of such biased agents are introduced into the scientific community.

Simulation Experiment 3: Seepage of denial?

This simulation experiment examined the effects of denial on the scientific community. Two classes of agents formed the population of 1,000: The mainstream scientists were unbiased ($S_S = 0$) and used a constant memory size of $M_S = 15$. A small proportion of the agents, represented by the parameter *ConProp* that was variously set to 3%, 10%, or 20%, were contrarian. Those agents used a memory size of $M_C = 3$ (to represent extreme focus on short-term fluctuations) and were biased, $S_C = .015$ (to exhibit persistent denial). To accentuate the differences between the two classes of agents, mainstream scientists relied on GISTEMP and contrarians relied on HadCRUT. (In reality, scientists would examine both those datasets and several additional products as well.)

All agents, irrespective of whether they were scientists or contrarians, communicated with each other 5 times after each data-sampling event. During those communication events, the representation of contrarians in the pool of communicators was varied (specified by *ConRep*) independently of their actual prevalence.

The results are shown in Figure 9. Consider first the top-left panel, which most closely represents the known composition of the scientific community. In this cell, 3% of the agents are biased contrarians. Like mainstream scientists, they are assumed to publish in the literature and thus communicate their opinions to the remainder of the community. This assumption appears realistic in light of the small but measurable number of contrarian articles that continue to appear in print (Cook et al., 2013).

The presence of contrarian voices does not prevent the scientific community from settling on the consensus position. Indeed, there is little evidence that the small number of contrarians had any effect on the scientific community, as indicated by the nearly complete overlap with the denial-free baseline from simulation experiment 1 (dashed gray line). Note, however, that this reflects extremely conservative assumptions because the contrarian agents communicate their estimate of the slope (β) *before* applying their bias (S_C). Their influence is thus limited to the cherry-picking associated with a small memory window.

The remaining 8 panels of Figure 9 explore the effects of increasing the proportion of contrarians (rows of panels) and their representation in communication (columns). Any increase in the proportion of contrarians beyond the empirically-established 3% of scientists involves the assumption that other, non-academic actors such as bloggers and think tanks contribute to the discussion in the scientific community. Given that blogs demonstrably contribute to science denial (for a discussion, see Lewandowsky, Oberauer, & Gignac, 2013; Lewandowsky, Cook, et al., 2015), in particular through harassment of scientists (e.g., Lewandowsky, Mann, Brown, & Friedman, 2016), this assumption appears plausible, although the extent of the influence of non-scientific actors on the scientific community is difficult to quantify. The assumption that contrarians are given disproportionate access to communication (i.e., the center and right columns of panels) is supported by content analysis of U.S. prestige media. During the period 1988-2002, more than half of that coverage was found to balance scientific and contrarian views (Boykoff & Boykoff, 2004). The share of contrarian discourse in the media peaked around 2009, with more than 3,000 articles in the U.S. media (Boykoff & Olson, 2013). In 2011-2012, contrarians were cited in 17% of media articles on climate change (Brüggemann & Engesser, 2017)

These analyses leave little doubt that contrarian voices are over-represented in public discourse, although the magnitude of that over-representation is uncertain. We therefore take no position on which of the 8 cells is most likely to be "correct." The next simulation experiment provides more constraints on which of those 8 cells appears most realistic in light of empirical data.

Overall, the pattern in Figure 9 clarifies that contrarian voices, even if amplified beyond their actual numbers, do not prevent the scientific community from settling on a consensus position. This reflects current reality, which has seen the formation of a pervasive scientific consensus notwithstanding intense contrarian activity. In all panels, scientists ultimately converge on complete acceptance of the climate change hypothesis. However, and perhaps most relevant in the present context, we also observed evidence for seepage (Lewandowsky, Oreskes, et al., 2015). Eight out of the 9 panels in Figure 9 exhibit an effect of seepage because the belief formation in the scientific community is delayed relative to the denial-free baseline. The one exception to this pattern is the top-left panel, which effectively assumes that the entire political apparatus that is enveloping the scientific community—from think tanks to bloggers to opinion writers—has no effect on scientific discourse because contrarian voices are limited to 3%. We find this assumption to be overly conservative.

Figure 10 shows the same results, but for 1990 onward only. This close-up on the last three decades is necessary because the alleged "pause" in warming from approximately 1998 onward (Figure 1) was cited as an example of possible seepage by Lewandowsky, Oreskes, et al. (2015). The figure offers limited support for that contention. Clear evidence for seepage arises only when the prevalence of communications between scientists and contrarians is at least 20%. For example, the center panel and bottom-left panel show evidence for seepage when the proportion is 20%, and the right-most column of panels shows strong evidence when the proportion is at 50%. In light of the clear evidence for amplification of contrarian voices, Figure 10 may well point to the presence of seepage, although the evidence is not as clear as for the overall delay of consensus formation in Figure 9.

Figures 9 and 10 also clarify that contrarians are oblivious to the evidence and to communications from mainstream scientists. Note that this outcome was not a foregone conclusion because even though simulation experiment 2 identified the need for a bias ($S_C = .015$) to model the persistence of denial, that was done for a community that exclusively involved biased agents. In the present experiment, by contrast, the 5 communication events associated with each data sampling event involved a population in which the vast majority of agents were unbiased. It follows that the contrarian agents here were exposed to far more information that could have swayed their opinions than in simulation experiment 2. Yet, even after receiving consistent trend information indicative of global warming for decades, the contrarians continued to resist the evidence (compare Figure 8 to the solid orange lines in all panels in Figure 9).

The asymmetry in influence between the two groups of agents is worth noting: On the one hand, scientists, with their unbiased view of the data, can be deleteriously impacted by poor and biased data selection (i.e., short-term trends) from an over-represented minority. Recall that communication among the agents involves transmission of their estimate of the trend, β, which is then used to update beliefs in the same manner as direct sampling of the data. Contrarians, on the other hand, are protected from the reverse effect because of their bias at the point of interpretation. Thus, whatever estimate of β a contrarian receives, the introduction of a bias (Equation 1) protects them from updating their knowledge in accordance with the evidence.

We next examine the impact of the commmunication regime introduced in this simulation, involving a majority of mainstream scientists and a small number of contrarians, on the general public.

Simulation Experiment 4: Science, denial, and the public

This simulation included a further 1,000 agents that represented the general public. Except for the addition of communication events with the general public, the experimental design and parameter settings were identical to the preceding simulation experiment.

The results are shown in Figure 11, using the same layout of panels as before. Of greatest interest here is the impact of denial on public opinion. Overall, it is clear that the presence of denial slows the public's convergence onto the scientific consensus position and sometimes prevents that convergence altogether. The details of that effect are informative. First, as shown in the left-most column of panels, increasing the proportion of contrarian voices alone is insufficient to prevent the public's recognition of the scientific consensus. Even with 20% of all interlocutors being contrarian, the public ultimately comes to share the belief of the majority of scientists. Second, for the public to remain unconvinced by the scientific evidence requires an over-representation of contrarian voices in public discourse. Specifically, public opinion in the U.S. at the moment is perhaps best captured by the data shown in the rightmost column of panels. Although it is not straightforward to map survey data into Bayesian probabilities, the finding that around 70% of the American public currently think that global warming is happening (e.g., Leiserowitz, Maibach, Roser-Renouf, Rosenthal, & Cutler, 2017) does not mesh well with values of $P(CC|E)$ near 1.0 that are observed for the general public in the left column or the top part of the center column in Figure 11. To capture public opinion, therefore, contrarian voices must be disproportionately represented, perhaps even to the extent that the number of mainstream scientific messages received by the public is exactly equal to the number of contrarian messages that deny climate change (right column).[2]

Are those assumptions warranted? There are several independent lines of evidence that support the notion that contrarian voices are disproportionately represented in public discourse. First, contrarian scientists report that they have greater media exposure than mainstream scientists (Verheggen et al., 2014). Second, the media's commitment to "balance" leads to coverage that often favours contrarian talking points (Boykoff & Boykoff, 2004; Brüggemann & Engesser, 2017). Third, certain media outlets in the U.S. have taken explicitly contrarian stands, including Fox News, the Washington Times, and the Wall Street Journal. Others, including Washington Post and New York Times, have regular columnists who promote contrarian positions. Fourth, contrarian organizations have regularly placed advertisements in leading newspapers to argue against climate action or question the science (Supran & Oreskes, 2017). Taken together, those sources of evidence suggest that the public—unlike the scientific community—may well receive an equal number of messages that affirm or deny climate change, respectively, from the interlocutors they are exposed to.

Exploration of parameters

The simulation experiments relied on two principal parameters: The memory size, M, and the bias in interpreting the perceived trend, S. It is useful to examine their effects on the moment-to-moment perception of the data, captured by the likelihood ratio (LR) in Equation 1. Figure 12 shows the effects of memory size on the LR for a simulation of the (unbiased) scientific community. The pattern is unsurprising but nonetheless informative. With a small memory buffer, the LR becomes highly variable and frequently dips below 1, implying a temporary reduction in the belief in the climate-change hypothesis. However, even with a small memory buffer, the temperature data contain a sufficiently strong signal for the LR to be, on average, above 1. This explains why a focus on short-term trends, often used by contrarians in public discourse to claim that warming has "stopped" (Carter, 2006), is insufficient to sustain disbelief in global warming without also introducing a bias. With a larger buffer, $M = 15$ and $M = 30$, the LR is consistently above 1 from the mid-1970s onward, in line with the identified onset point of global warming (Cahill, Rahmstorf, & Parnell, 2015).

Figure 13 examines the effect of the bias parameter, S, on the LR. The most notable aspects of those results is that even with a "cooling" bias of .015, the LR does not fall much below 1 during the period of global warming (from mid 1970 onward). The persistence of denial may therefore be best understood as a failure to update an (inappropriately-skeptical) belief in light of evidence.

General Discussion

This paper explored the reasoning components that underpin the potential for disbelieving climate change when faced with the actual observed temperatures. All agents, whether mainstream scientists, contrarians, or the public, revised their beliefs in accordance with Bayesian principles, the gold standard of rational belief formation (see Equations 1 and 2). Our simulations yielded several insights: (a) unbiased agents necessarily acquire belief in the climate-change hypothesis even from an initial position of extreme skepticism; (b) to persist with denial, agents must be biased; (c) the presence of such biased agents can delay, but not prevent, belief formation in the scientific community; (d) the presence of contrarian voices, especially when disproportionately represented, can prevent the public from acquiring the scientific consensus position. We take up the implications of those results later, after we acknowledge and discuss several limitations of the present work.

Potential limitations and avenues for future exploration

Our simulations aimed to balance parsimony with realism. We achieved parsimony by limiting agents to two free parameters, M and S, with the remainder of their architecture being fixed by Bayesian principles. Those tight constraints on the architecture limited the realism of our results. For example, although simulation experiment 4 yielded a realistic estimate of current public opinion with plausible assumptions about denial (Figure 11), the simulated public acceptance of climate change lagged far behind the American public, which 20 years ago endorsed the climate-change hypothesis to a similar extent than is seen now (e.g., Brulle et al., 2012).

Several aspects of our model may have contributed to this quantitative mismatch. For example, the model excluded a number of mechanisms that are known to affect the public's reasoning about climate change, such as perceived source credibility (Hahn, Harris, & Corner, 2009; Harris, Hahn, Madsen, & Hsu, 2016), or worldviews and political attitudes (e.g., Hamilton et al., 2015; Lewandowsky, Gignac, & Oberauer, 2013). The model also focused on a single scientific updating process, and other regimes might be worth considering in the future. For example, scientists may consider the long-term record only, looking for some kind of meaningful change point in the warming trend instead of recomputing it from observations in the presumed memory window. Moreover, given that scientists' careers do not extend across the time span simulated here (nearly 70 years), some inter-generational transmission process must exist that permits junior scientists to build on existing knowledge in the discipline without monitoring the data for decades.

Inter-generational processes can readily be modeled in an agent-based framework (Holman & Bruner, 2017).

We focused on GMST (Figure 1) as the only source of evidence for climate change. Although GMST is a primary climatic indicator, and arguably the one that is discussed most often in public, it is only one among many. Other indicator variables include sea level rise, cryosphere variables such as the mass balance of glaciers, biological indicators such as species migration, and so on (e.g., Hartmann et al., 2013; Rhein et al., 2013; Vaughan et al., 2013). In reality, scientists consider all of those variables together, and it is their converging support for the same conclusion, known as consilience (Oreskes, 2007), that buttresses the scientific consensus position. Although denialist talking points are known to extend to those other indicator variables (Lewandowsky, Ballard, et al., 2016), it remains to be seen how seepage and influence play out in a multivariate environment.

Implications and potential interventions

Irresistible evidence for global warming

Our simulations showed that unbiased agents necessarily acquire belief in the climate-change hypothesis, even when they start from an initial position of extreme skepticism and even when they rely on unduly short temperature trends. This result meshes well with a previous analysis of the success of hypothetical bettors that placed bets on global temperatures at various points in history. That analysis found that since 1970, any bet against warming—even those involving cherry-picking of short-term cooling trends—would have been unsuccessful (Risbey, Lewandowsky, Hunter, & Monselesan, 2015).

The corollary result, that agents must be biased in order to persist with denial, also meshes well with existing results. For example, the need for biased processing is compatible with the fact that denial is a political operation rather than a scientific endeavour (Dunlap & McCright, 2011). Biased processing is also revealed when contrarian talking points are subjected to a blind expert test (Lewandowsky, Risbey, & Oreskes, 2016; Lewandowsky, Ballard, et al., 2016). In those studies, climate data and contrarian claims about those data (e.g., "warming has stopped") were translated into another domain, for example by presenting GMST data as "world agricultural output." Expert economists and statisticians then judged the contrarian claims to be misleading while endorsing the interpretation advanced by mainstream scientists.

Although we modeled denial by including a bias parameter, it does not follow that resistance to evidence is "irrational." On the contrary, denial has been identified as a rational political operation of considerable effectiveness (Lewandowsky, Cook, & Lloyd, 2016), and even under a fully Bayesian approach, resistance to evidence can be modeled by inclusion of auxiliary hypotheses (Cook & Lewandowsky, 2016; Gershman, 2018).

Seepage and influence

One purpose of the simulations was to test the idea that denialist talking points may seep into the scientific community, perhaps altering the way in which scientists interpret data (Lewandowsky, Oreskes, et al., 2015). The evidence for this was clear in general, but more mixed in the specific context of the alleged "pause." On the one hand, consensus formation was delayed by the presence of denial whenever the functional proportion of contrarian voices exceeded their nominal proportion of 3% (Figure 9). As we argued earlier, the known machinery of denial (e.g., blogs, think tanks, opinion pieces) most likely amplifies contrarian voices beyond their actual number, and so it seems warranted to conclude that denial *can* have an effect on the scientific community. On the other hand, an effect of seepage during the period of the presumed "pause" in warming was only observed when liberal assumptions were made about the influence of denial (viz., 20% or more of all voices being heard by scientists are contrarian).

It must be noted that our model of the scientific community was highly idealized. Each agent was fair and unbiased and accurately interpreted the data using a climatologically reasonable window. Nonetheless, the injection of biased contrarian voices into this idealized community was sufficient to delay consensus formation. This occurred without any bad faith, corruption, dishonesty, or bias on the part of scientists, putting to rest a potential criticism that the seepage notion entails an accusatory or critical stance against scientists. Other related work has also shown that the pernicious effects of industry funding of research (e.g., the death toll associated with class-I antiarrhythmic drugs; Holman, 2017) can arise without corruption of individual scientists, simply from methodological diversity and a merit-based system (Holman & Bruner, 2017). Similarly, Weatherall, O'Connor, and Bruner (2018) presented an agent-based model of the tobacco industry's efforts to undermine the scientific evidence about the harm from smoking. The model relied on a two-pronged propagandistic effort: first, promoting and sharing of independent research that conformed to the industry's position, and second, funding of additional research with selective publication of the results. Both lines of attack have been well documented by historians (Oreskes & Conway, 2010; Proctor, 2011). Weatherall et al. (2018) showed that their selective-sharing model could explain how policy makers failed to recognize the seriousness of the harm from tobacco, and how journalists, by engaging in "fair" reporting, inadvertently amplified industry's impact on public opinion. The model showed that there was no need for the tobacco industry to engage in outright fraud or conduct biased research of their own. Industry could influence public policy by the less expensive and more furtive strategy of selective sharing and communicating.

In summary, there are now multiple demonstrations that distortions of scientific practice, including but not limited to seepage, can be observed without any corruption or bias of any individual scientist. One implication of our reliance on an idealized scientific community is that our simulations likely provided a lower-bound estimate of seepage. Any departure from this ideal, for example by introducing scientists with their own biases, might lead to greater discernible seepage.

Turning to the effects of denial on the public, there is no doubt that the presence of contrarian voices can prevent the public from fully acquiring the scientific consensus position (Figure 11). This result is unsurprising, although what is notable is that the public remains misinformed about the scientific consensus only when contrarian voices are amplified beyond their actual proportion. It is only when scientific information and denialist talking points are balanced (or nearly so), that the public will fail to converge on the consensus position. Several analyses have confirmed that contrarian voices are over-represented in media discourse (Boykoff & Boykoff, 2004; Boykoff & Mansfield, 2008; Brüggemann & Engesser, 2017).

Our results on seepage and influence fit within the larger context of research on a minority's ability to sway majority opinion (Crano & Seyranian, 2009; Xie et al., 2011, 2012). One finding from this research is that a committed minority that is immune to influence can reverse the prevailing majority opinion under certain conditions (for a discussion, see Wiesner et al., 2019). Theoretical work suggests that a minority of 10% is sufficient to flip a majority (Xie et al., 2011), and experimental evidence suggest that around 25% are needed to reverse an initial consensus opinion (Centola, Becker, Brackbill, & Baronchelli, 2018). Although we exposed our scientific community to considerable dissent by a minority that was immune to evidence (some conditions of simulation experiment 4), we did not observe a reversal of the consensus opinion. This resilience, relative to other modeled communities, likely arose from the presence of independent evidence (i.e., the observed temperature trends) which prevented intransigent contrarian opinions from swaying the majority.

Potential interventions

Our model explored specific questions about belief formation in a contested environment. The model also points to a deeper and more general problem: how to model and potentially reduce the dissemination of misinformation in social systems. Humans constantly share their beliefs and information. While this allows for debate, reasoning, and education, such social networks also support the dissemination of sub-standard or downright false information. Our model can point to potential remedial measures: In simulation experiment 4, we found that when contrarian views are communicated to the public in proportion to their actual prevalence, the public will not be thwarted from accepting the scientific consensus position. This result suggests that one effective intervention in public discourse would be to avoid the disproportionate amplification of contrarian voices in media discourse. Fahy (2018) reports several encouraging developments in journalistic practice that may meet this challenge.

Further work could build on this foundation by specifying the media-intermediary processes in more detail (e.g., how people select news sources based on political preference, or how people's perceptions of credibility affect the updating process). Madsen and Pilditch (2018) have successfully deployed a Bayesian source-credibility model to investigate mass-persuasion attempts, pointing to ways in which a more nuanced model of public opinion on climate change might be constructed. Hills (2018) outlined how cognitive heuristics can contribute to polarization and the spread of misinformation. Recommendations to overcome those problems were provided by Hills (2018) and Lewandowsky, Ecker, and Cook (2017).

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Footnotes

[1] In reality, scientists had access to both products and their judgment in all likelihood would have rested on an aggregation of information from both datasets.

[2] The three panels in the right column are identical. This is no accident because when the public representations of views are set to be identical (i.e., 50-50 in each panel), the *actual* proportion of contrarians in the community no longer matters.

Figure Captions

Figure 1. Global mean surface temperature (GMST) anomalies from two datasets. GISS = NASA GISTEMP (Hansen et al., 2010); HadCRUT4 = UK Met Office (Morice et al., 2012). The datasets use slightly different climatological baselines (GISTEMP: 1951–1980; HadCRUT: 1961-1990). To align the datasets for display purposes, all anomalies here are re-baselined to the period 1981–2010.

Figure 2. Observed magnitude of temperature trends as a function of vantage year and the number of years included in the computation of the trend. Trends are capped at $\pm 1K$ for plotting. For each vantage year (columns), trends are computed for all possible windows between 3 and 25 years duration (rows), all of which end with the particular vantage year. The dots indicate which trends are significant ($p < .05$) in an ordinary least squares analysis of annual means, and the horizontal dashed line indicates the number of years that must be included for the trend to be significant from all vantage points. **A**: Data are HadCRUT4 (Morice et al., 2012). **B**: Data are GISTEMP (Hansen et al., 2010).

Figure 3. **a**. Overview of agent-based model with communication and updating cycles. See text for details. **b**. Summary of simulation experiments. See text for details.

Figure 4. Illustration of regression slope calculations for a typical scientist agent (subscript S) and a contrarian agent (subscript C). The scientist possesses a larger memory window ($M_S = 15$) than the contrarian ($M_C = 3$) from t_0 (the current year) back through time. This leads to a difference in calculated regression slopes, where β_S reflects the long-term warming trend, whereas β_C reflects a short-term cooling trend.

Figure 5. Illustration of how perceived regression slopes are converted into likelihood ratios (LR) that are then used for belief updating according to Equation 2. The scientist agent provides β_S, and because the scientist is unbiased, the positive β_S value is converted

to a positive likelihood ($LR_S > 1$), providing support for the climate change hypothesis. By contrast, the positive value of the skew parameter ($S_C = .1$) for the contrarian agent accentuates the already negative slope (β_C) as even greater evidence against climate change ($LR_C < 1$) For illustrative purposes, the value of S_C is considerably larger here than in the simulations.

Figure 6. Results of Simulation Experiment 1 involving only a community of scientists. All agents are unbiased ($S_S = 0$) and consider data either from GISTEMP (left panel) or HadCRUT (right panel). Each plotted line represents a different memory size (M_S); see legend. The vertical dashed lines mark release dates of IPCC consensus reports, from the First Assessment Report (FAR) through the Fifth Assessment Report (AR5).

Figure 7. Results of Simulation Experiment 1 involving a scientific community together with a general public. See text for details of how agents communicate with each other. All agents are unbiased ($S_S = 0$) and consider data either from GISTEMP (left panel) or HadCRUT (right panel). The vertical dashed lines mark release dates of IPCC consensus reports, from the First Assessment Report (FAR) through the Fifth Assessment Report (AR5).

Figure 8. Results of Simulation Experiment 2. Agents are either unbiased ($S_C = 0$; top row of panels) or are biased to downplay the observed trend ($S_C = .015$; bottom row of panels). Agents consider data either from GISTEMP (left column of panels) or HadCRUT (right). Each plotted line represents a different memory size (M_C); see legend. The vertical dashed lines mark release dates of IPCC consensus reports, from the First Assessment Report (FAR) through the Fifth Assessment Report (AR5).

Figure 9. Results of Simulation Experiment 3. Each panel reports a different condition of the experiment, with the proportion of contrarians *ConProp* varying across rows, and the

level of representation of contrarians *ConRep* varying across columns. In each panel, there are 1,000 agents altogether, some of which are set to be contrarian (i.e., $M_C = 3, S_C = .015$). Acceptance of the climate change hypothesis, $P(CC|E)$, is shown separately for mainstream scientist agents (solid blue line) and contrarian agents (solid orange). The variability across replications is indicated in the thickness of the blue lines. For comparison, the belief acquisition without the presence of contrarians (i.e., from simulation experiment 1) is shown by gray dashed lines. The vertical dashed lines mark release dates of IPCC consensus reports, from the First Assessment Report (FAR) through the Fifth Assessment Report (AR5).

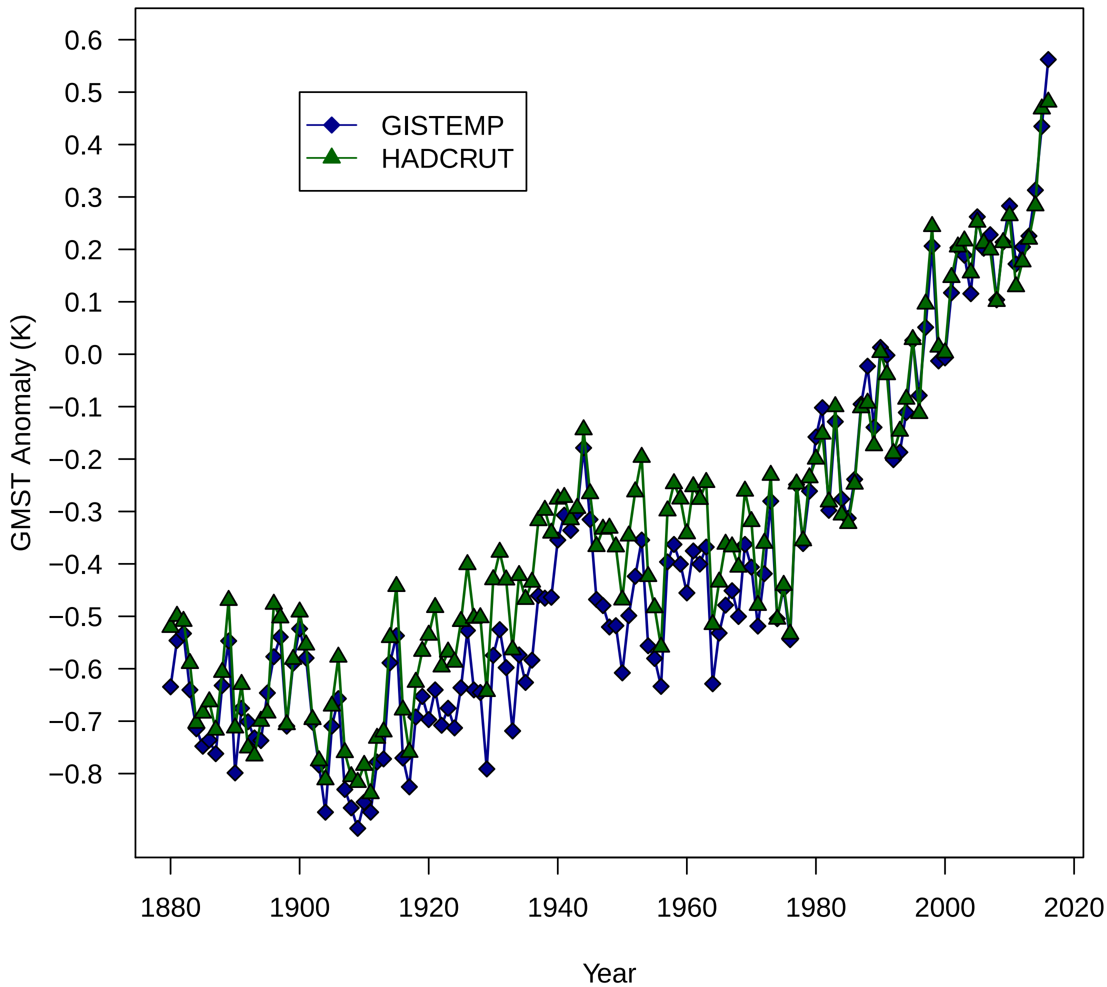
Figure 10. Results of Simulation Experiment 3, shown for 1990 onward. Each panel reports a different condition of the experiment, with the proportion of contrarians *ConProp* varying across rows, and the level of representation of contrarians *ConRep* varying across columns. In each panel, there are 1,000 agents altogether, some of which are set to be contrarian (i.e., $M_C = 3, S_C = .015$). Acceptance of the climate change hypothesis, $P(CC|E)$, is shown separately for mainstream scientist agents (solid blue line) and contrarian agents (solid orange). The variability across replications is indicated in the thickness of the blue lines. For comparison, the belief acquisition without the presence of contrarians (i.e., from simulation experiment 1) is shown by gray dashed lines. The vertical dashed lines mark release dates of IPCC consensus reports, from the First Assessment Report (FAR) through the Fifth Assessment Report (AR5).

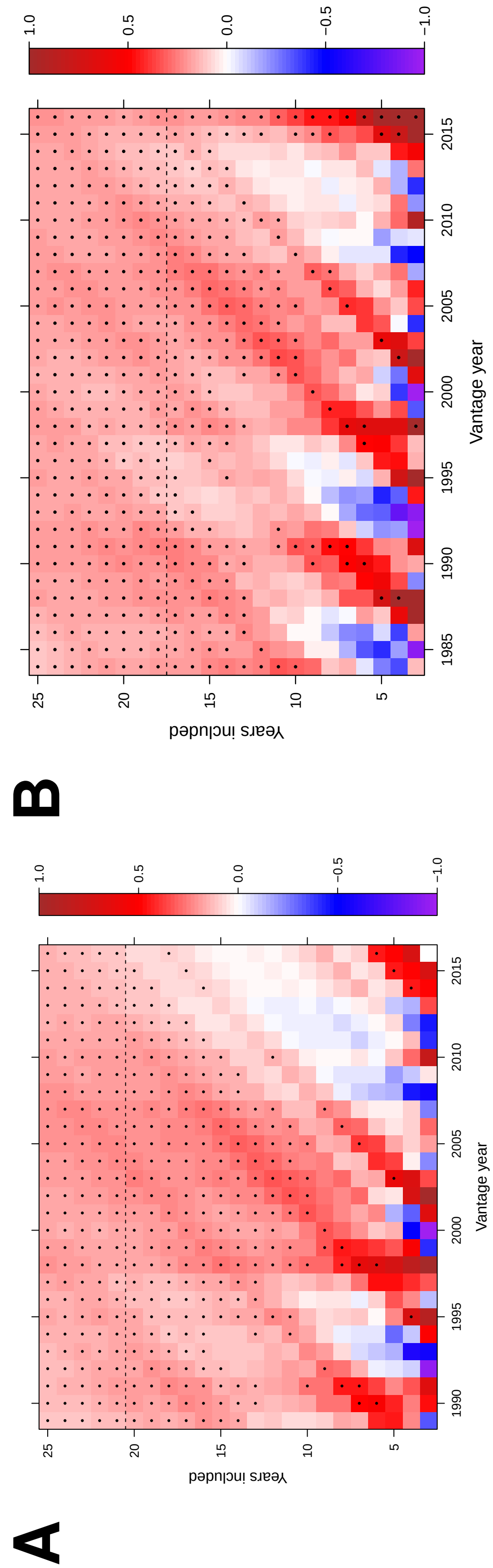
Figure 11. Results of Simulation Experiment 4. Each panel reports a different condition of the experiment, with the proportion of contrarians *ConProp* varying across rows, and the level of representation of contrarians *ConRep* varying across columns. In each panel, there are 1,000 agents that represent mainstream scientists and contrarians, and a further 1,000 agents that represent the general public. Results are shown separately for scientists,

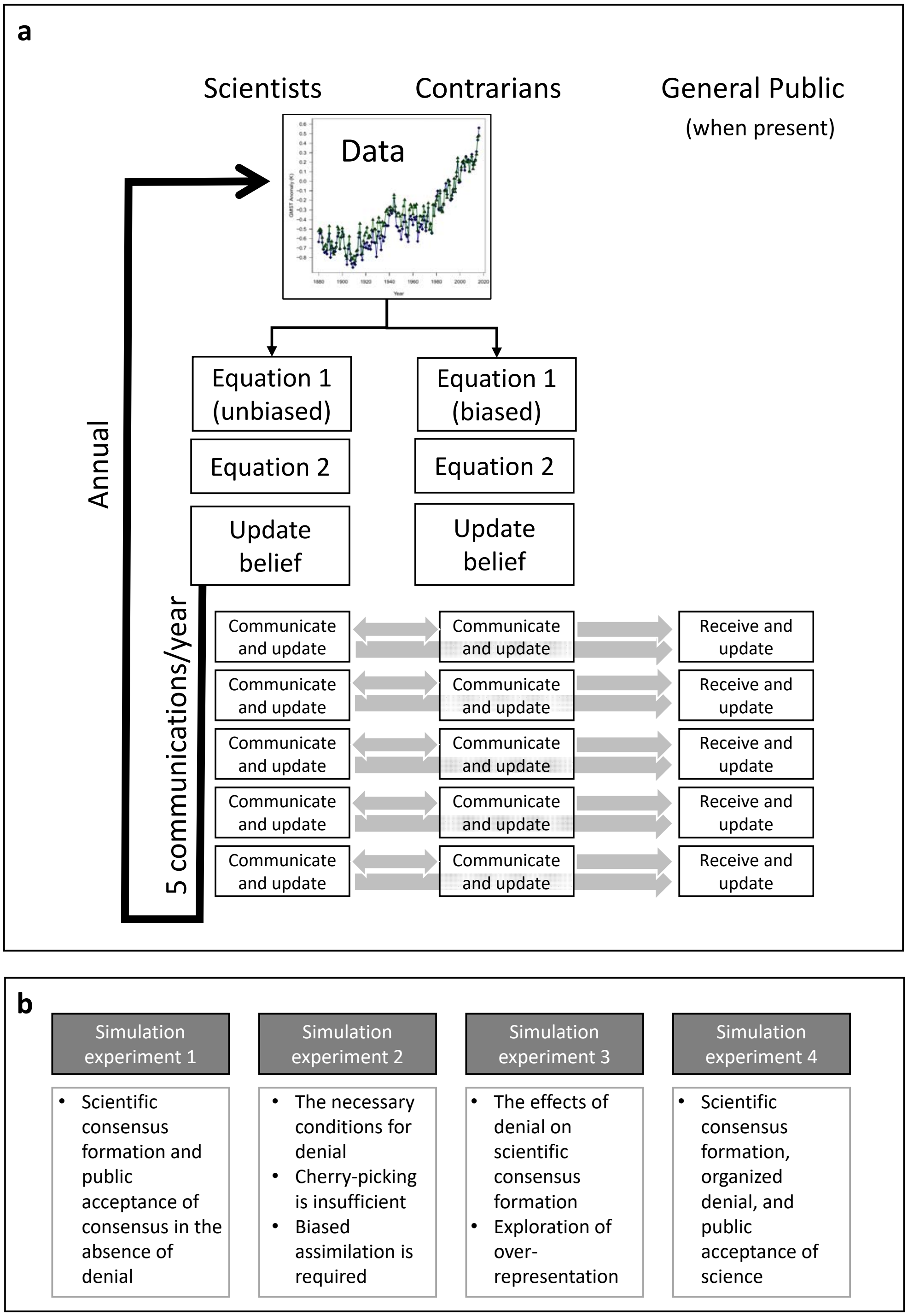
contrarians, and the general public. The variability across replications is indicated by the thickness of the lines. The vertical dashed lines mark release dates of IPCC consensus reports, from the First Assessment Report (FAR) through the Fifth Assessment Report (AR5).

Figure 12. Values of LR (Equation 1) observed during simulation experiment 1 for different values of M. The horizontal line at 1.0 represents completely ambiguous evidence that leaves current belief unchanged during updating (Equation 2). All agents are unbiased, $S = 0$, and consider data either from GISTEMP (left panel) or HadCRUT (right panel).

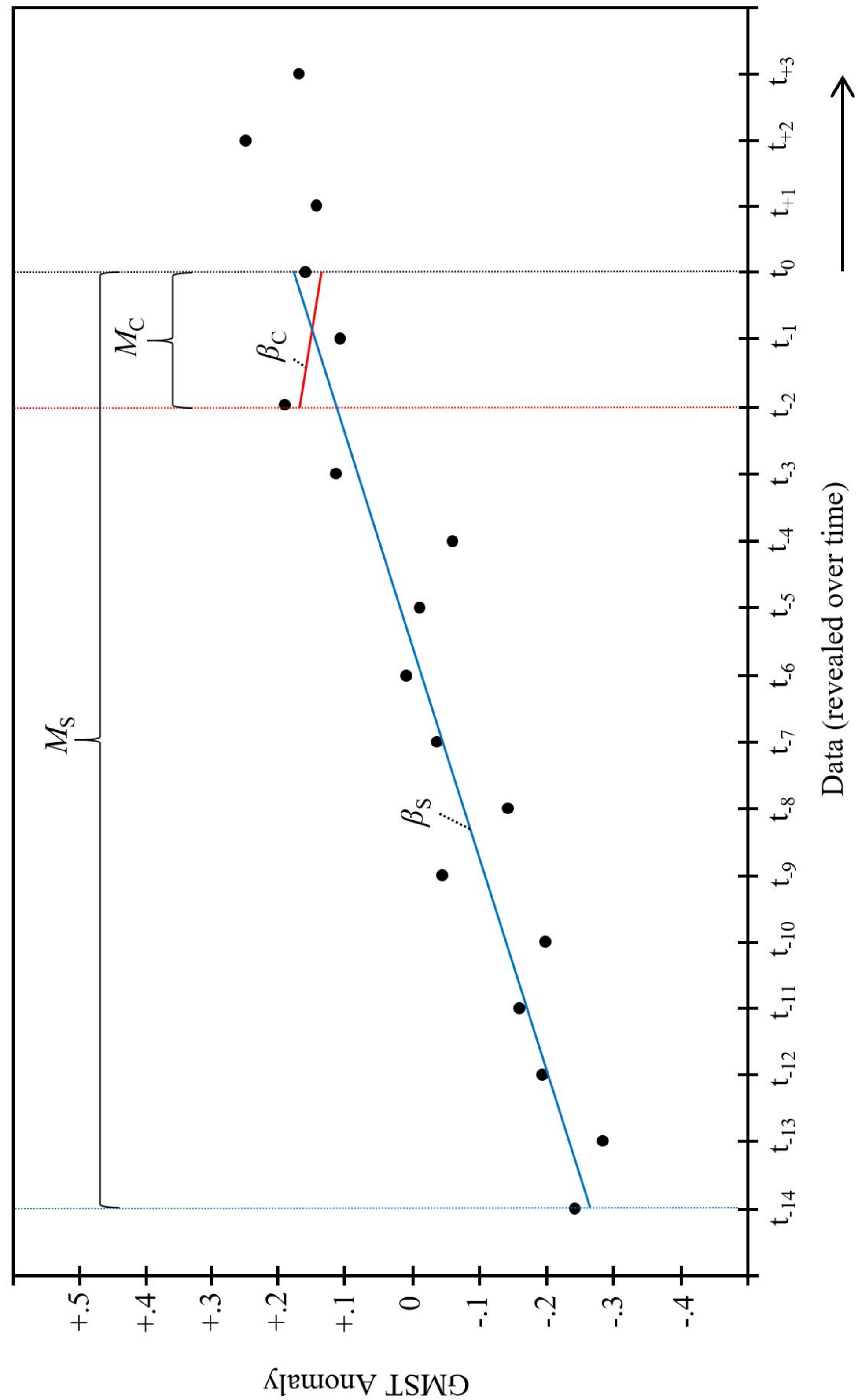
Figure 13. Values of LR (Equation 1) observed with two different sizes of the memory buffer; $M = 3$ in the top row of panels, $M = 15$ in the bottom row. Each panel plots the observed LR for different values of the bias parameter, S. The horizontal line at 1.0 represents completely ambiguous evidence that leaves current belief unchanged during updating (Equation 2). All agents consider data either from GISTEMP (left column of panels) or HadCRUT (right).

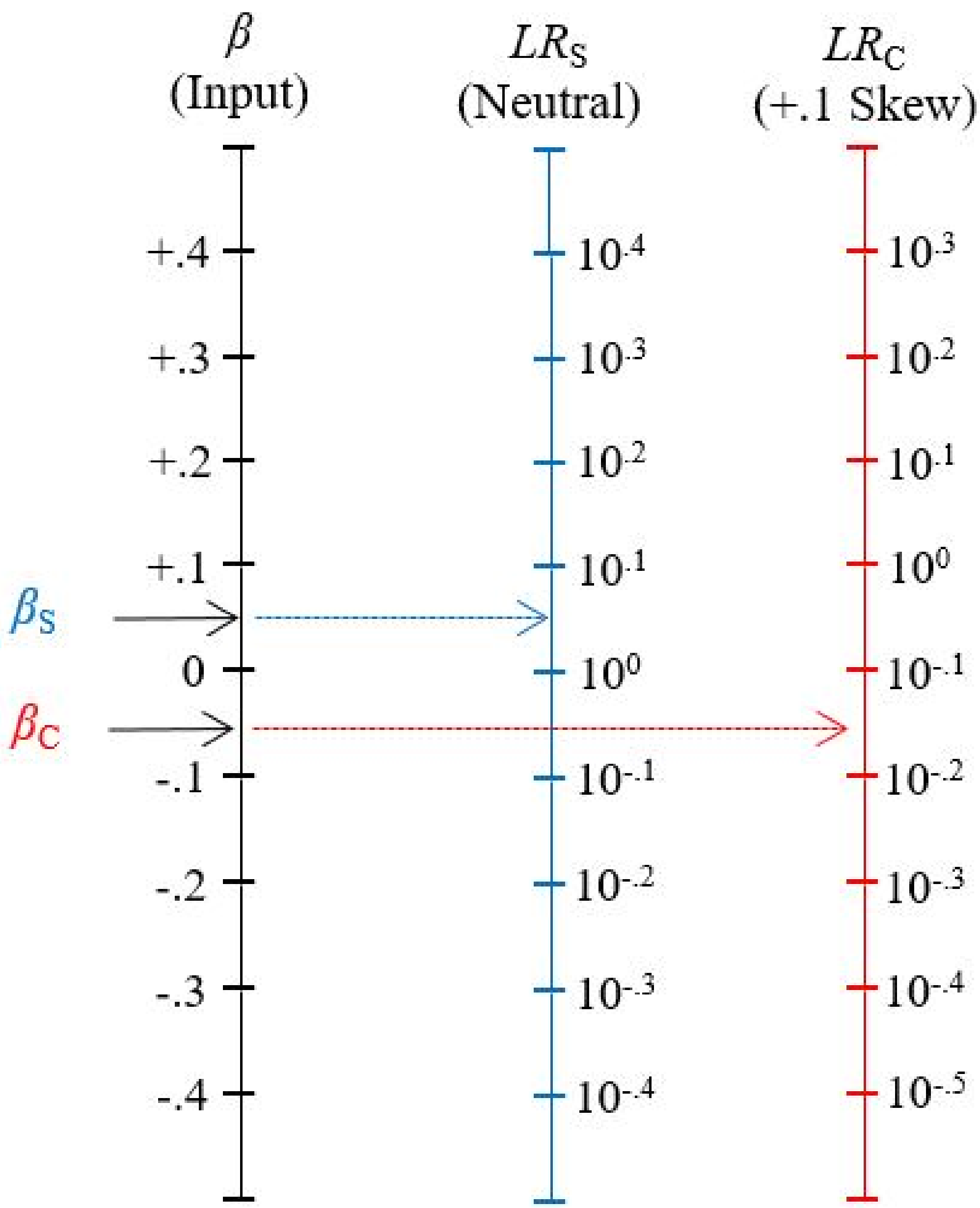

GISTEMP
HADCRUT
GMST Anomaly (K)
0.6
0.5
0.4
0.3
0.2
0.1
0.0
−0.1
−0.2
−0.3
−0.4
−0.5
−0.6
−0.7
−0.8
1880
1900
1920
1940
1960
1980
2000
2020
Year


A
B
Years included
Vantage year
25
20
15
10
5
1985
1990
1995
2000
2005
2010
2015
1.0
0.5
0.0
−0.5
−1.0

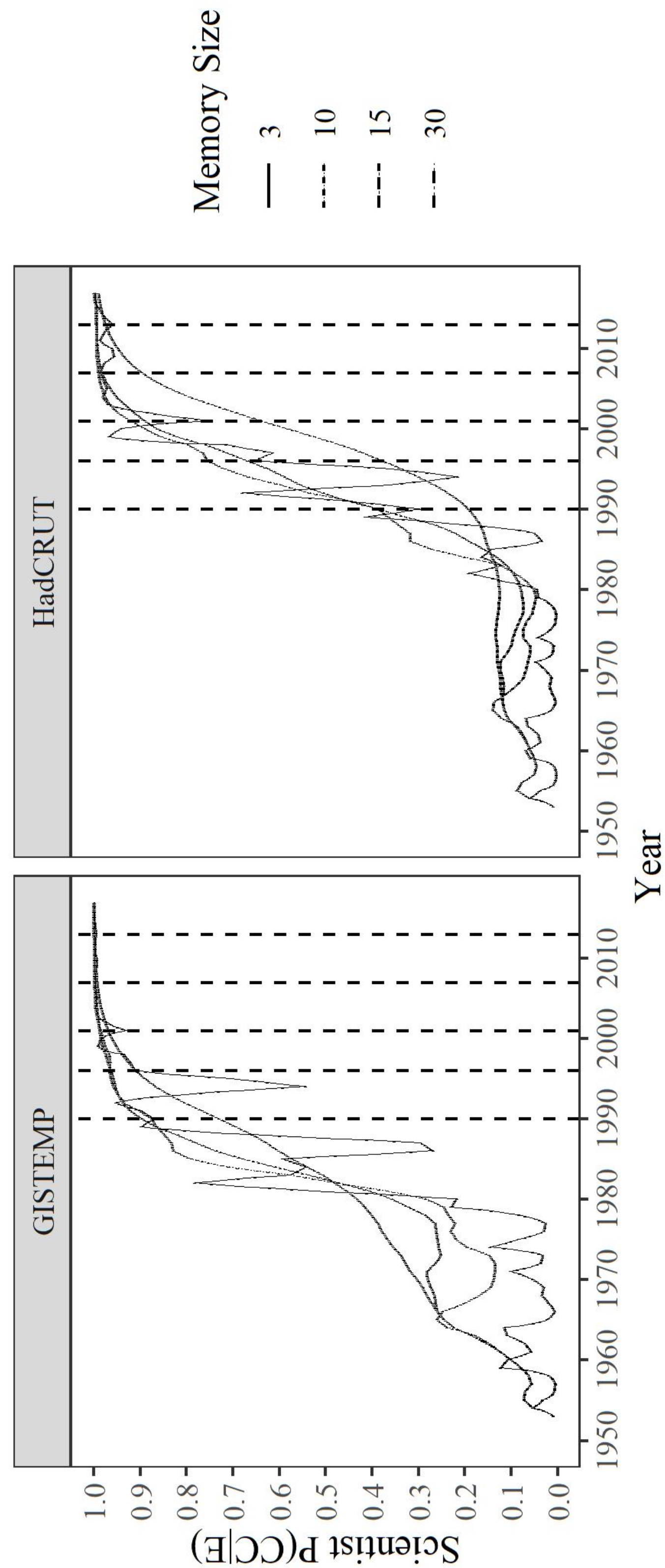

a
Scientists
Contrarians
General Public
(when present)
Data
Annual
Equation 1 (unbiased)
Equation 1 (biased)
Equation 2
Equation 2
Update belief
Update belief
5 communications/year
Communicate and update
Communicate and update
Receive and update
Communicate and update
Communicate and update
Receive and update
Communicate and update
Communicate and update
Receive and update
Communicate and update
Communicate and update
Receive and update
Communicate and update
Communicate and update
Receive and update
b
Simulation experiment 1
• Scientific consensus formation and public acceptance of consensus in the absence of denial
Simulation experiment 2
• The necessary conditions for denial
• Cherry-picking is insufficient
• Biased assimilation is required
Simulation experiment 3
• The effects of denial on scientific consensus formation
• Exploration of over-representation
Simulation experiment 4
• Scientific consensus formation, organized denial, and public acceptance of science

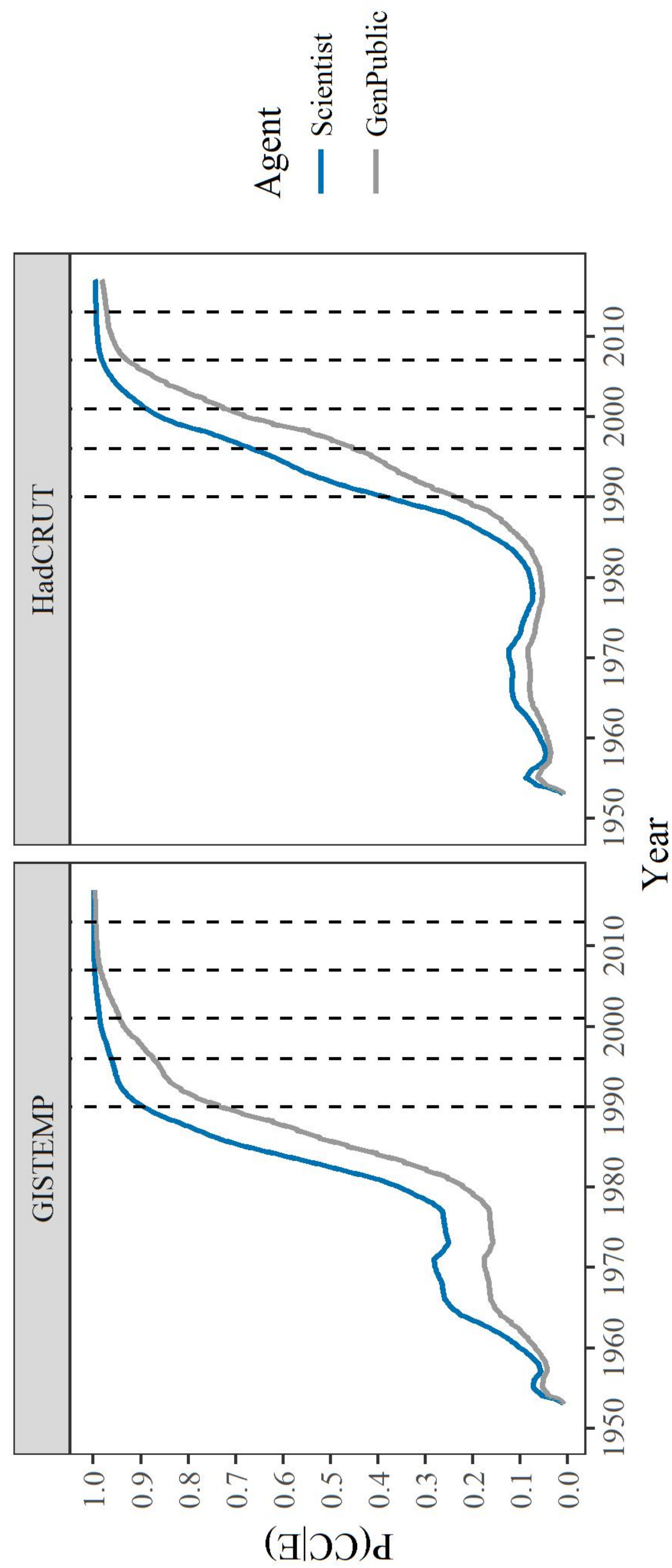
Influence and seepage, Figure 4



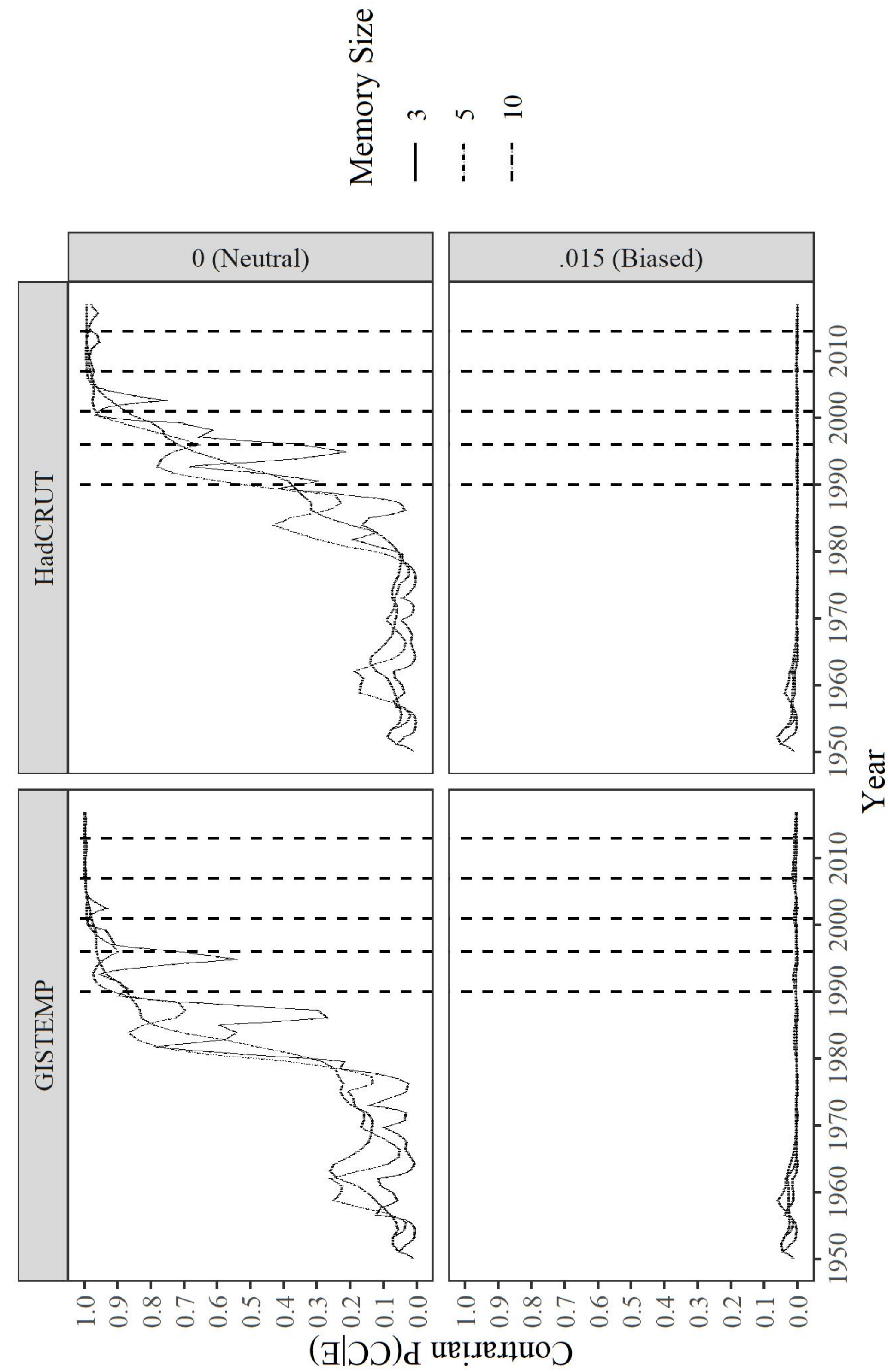


β
(Input)
LRS
(Neutral)
LRC
(+.1 Skew)
+.4
+.3
+.2
+.1
0
-.1
-.2
-.3
-.4
βS
βC
10.4
10.3
10.2
10.1
10^0
10-.1
10-.2
10-.3
10-.4
10.3
10.2
10.1
10^0
10-.1
10-.2
10-.3
10-.4
10-.5

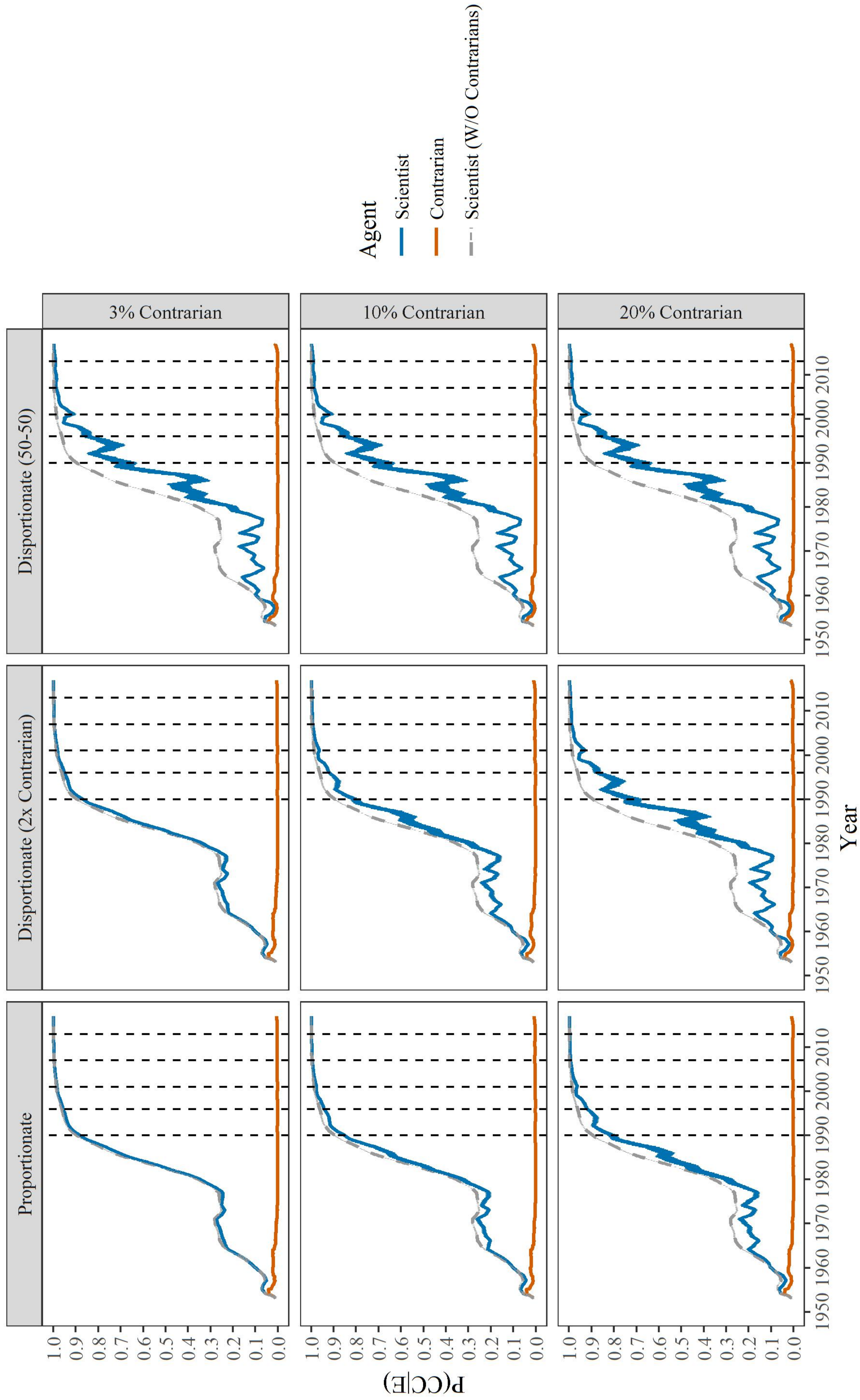

GISTEMP
HadCRUT
Scientist P(CC|E)
Year
Memory Size
3
10
15
30
1950
1960
1970
1980
1990
2000
2010
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1.0

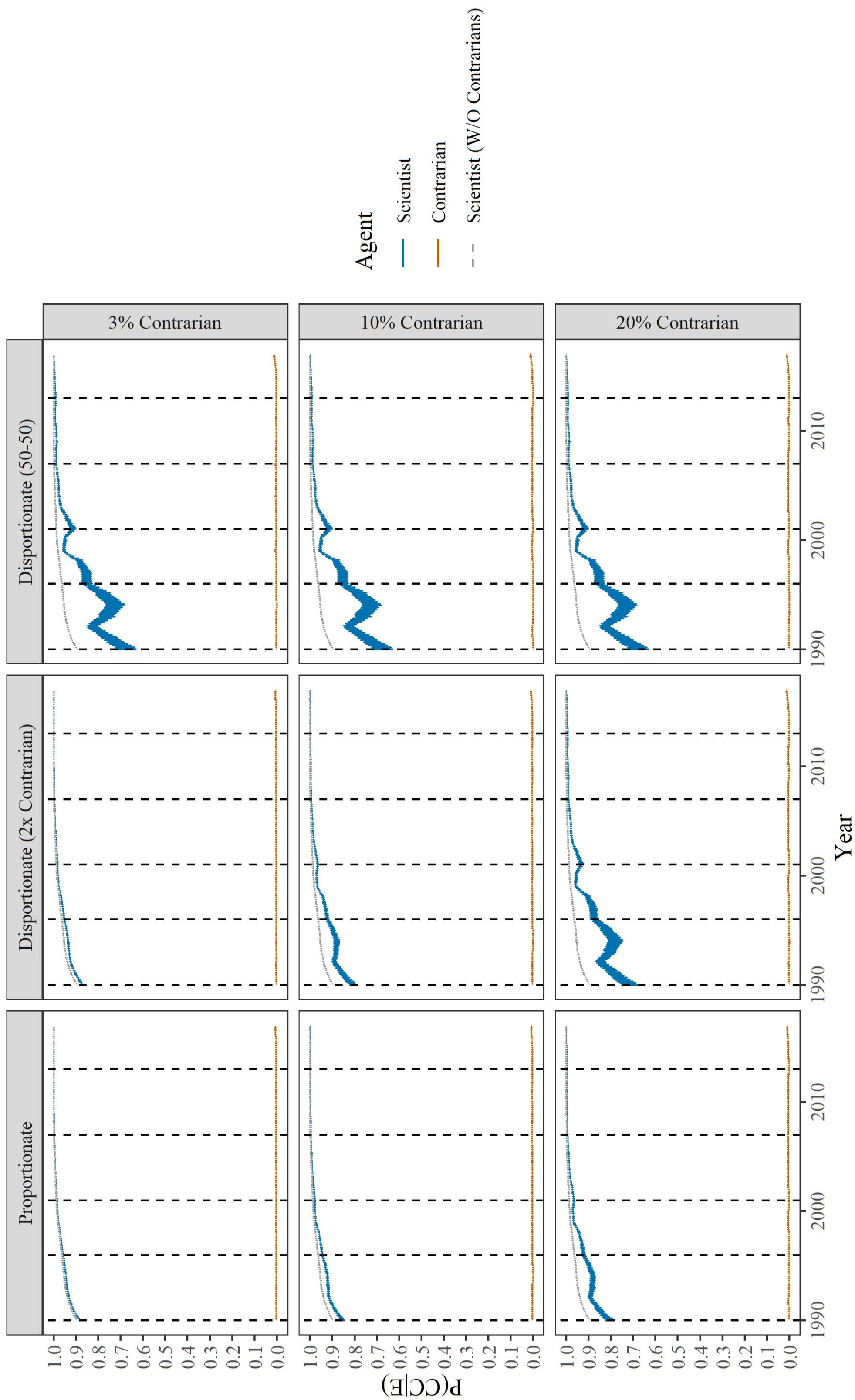


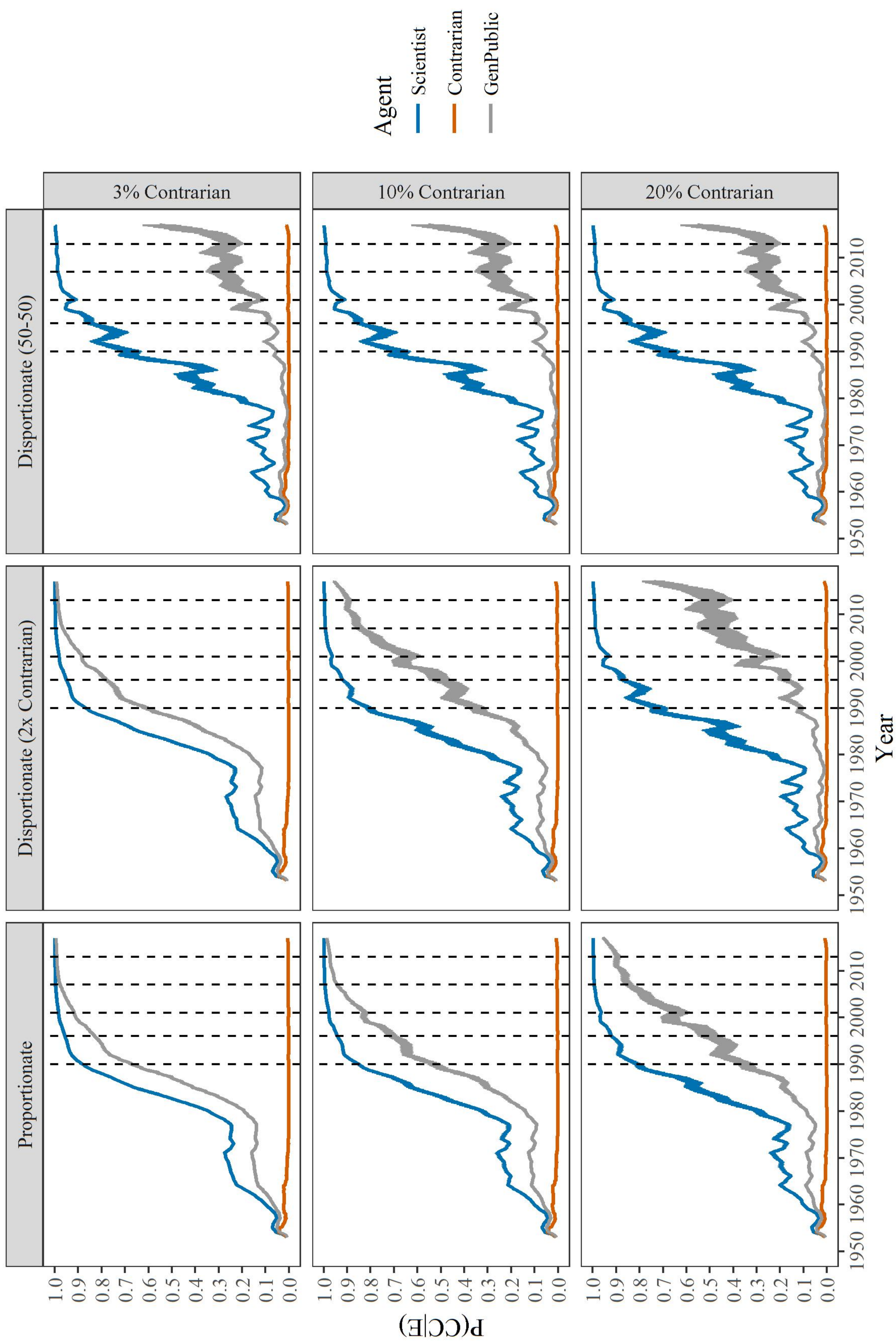
GISTEMP
HadCRUT
P(CC|E)
1.0
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
1950
1960
1970
1980
1990
2000
2010
Year
Agent
Scientist
GenPublic

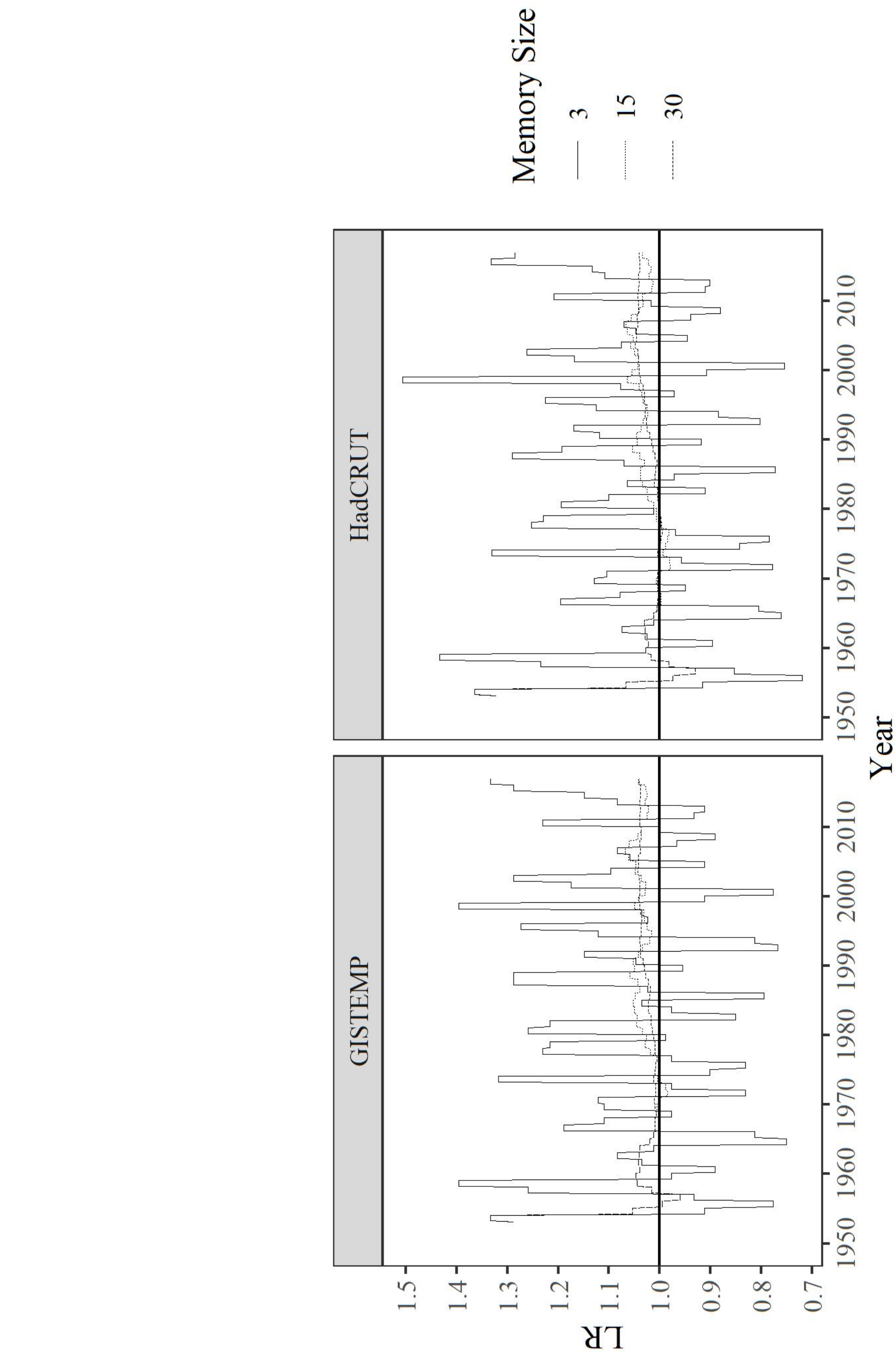


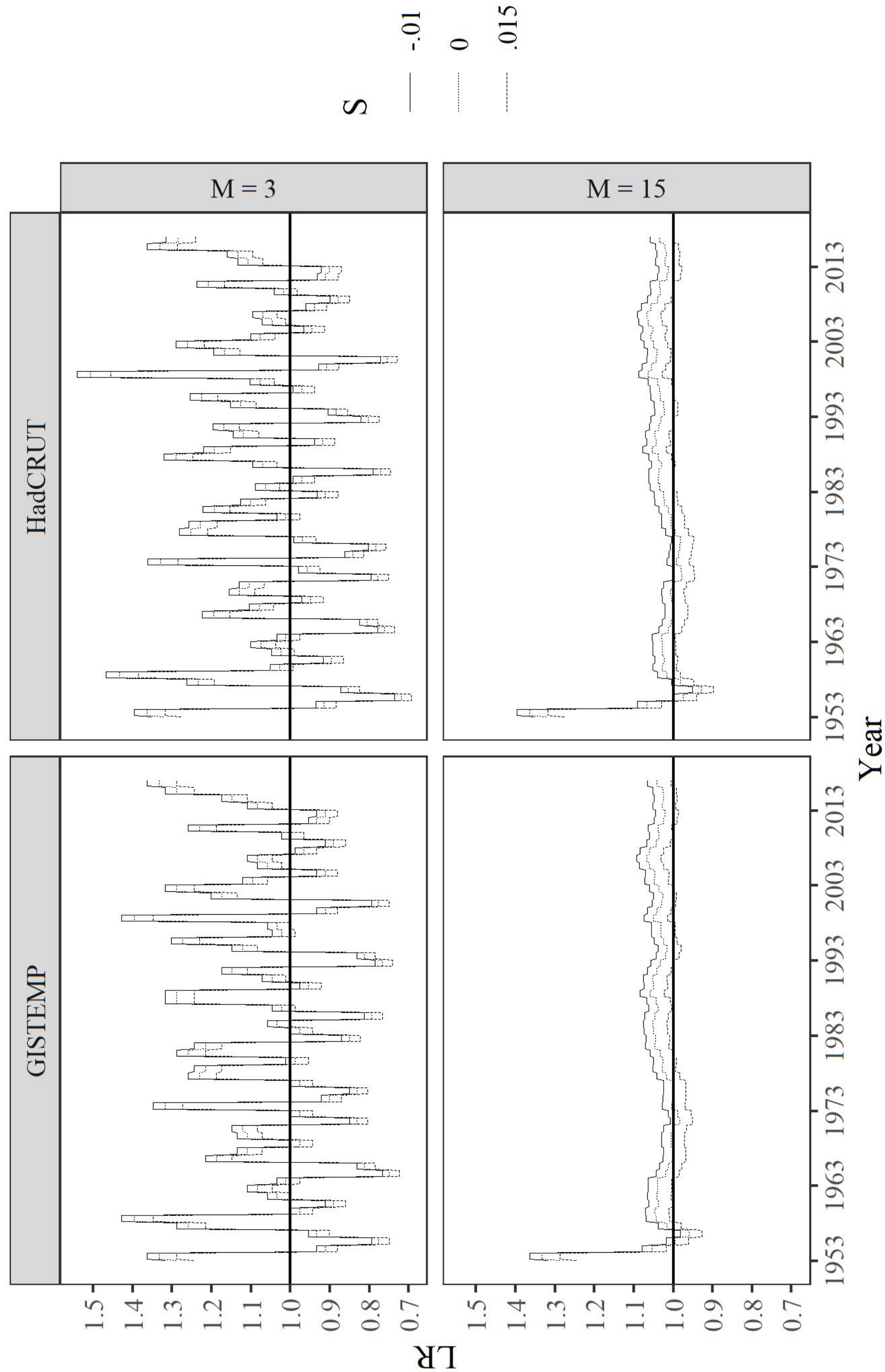
Memory Size
3
5
10
0 (Neutral)
.015 (Biased)
GISTEMP
HadCRUT
Contrarian P(CC|E)
1.0
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
1950
1960
1970
1980
1990
2000
2010
Year


Proportionate
Disportionate (2x Contrarian)
Disportionate (50-50)
3% Contrarian
10% Contrarian
20% Contrarian
Agent
Scientist
Contrarian
Scientist (W/O Contrarians)
Year
P(C|E)


Proportionate
Disportionate (2x Contrarian)
Disportionate (50-50)
3% Contrarian
10% Contrarian
20% Contrarian
P(CC|E)
Year
1990
2000
2010
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1.0
Agent
Scientist
Contrarian
Scientist (W/O Contrarians)


Agent
Scientist
Contrarian
GenPublic
Proportionate
Disportionate (2x Contrarian)
Disportionate (50-50)
3% Contrarian
10% Contrarian
20% Contrarian
P(CC|E)
Year
1950 1960 1970 1980 1990 2000 2010
0.0 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9 1.0


GISTEMP
HadCRUT
LR
Year
Memory Size
3
15
30


GISTEMP
HadCRUT
M = 3
M = 15
LR
Year
S
-.01
0
.015